DEVELOPMENTAL DYSGRAPHIA DIAGNOSIS BASED ON QUANTITATIVE ANALYSIS OF ONLINE HANDWRITING

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Abstract: The prevalence of handwriting difficulties among school-aged children is around 10 – 30 %. Until now, there is no objective method to diagnose and rate developmental dysgraphia (DD) in Czech Republic. The goal of this study is to propose a new method of objective DD diagnosis based on quantitative analysis of online handwriting. For this purpose, we extracted a set of spatial, temporal, kinematic and dynamic features from three handwriting tasks. Consequently, we performed a correlation analysis between these features and score of handwriting proficiency screening questionaire (HPSQ), in order to identify parameters with a good discrimination power. Using random forests classifier in combination with quantification of alphabet writing task, we reached nearly 77 % classification accuracy (75 % sensitivity, 80 % specificity). This pilot study proves the possibility of automatic DD diagnosis in children cohort writing with cursive letters.

Keywords: developmental dysgraphia, digitizing tablet, online handwriting, quantitative analysis, diagnosis

1 INTRODUCTION

Handwriting is a complex human activity involving rapid sequencing of movements in time, which reflects the relationship between planning and product generation [4]. A mastery of lower level transcription skills such as handwriting is needed for idea conceptualization and production of high-level content text [5]. Children with development dysgraphia (DD) didn't succeed in developing proficient handwriting. Their written product accompanies poor legibility and they put lot of effort into handwriting process [2, 12] which leads to inadequate handwriting speed. The prevalence of DD among school-aged children is around 10 – 30 % [6].

Handwriting proficiency screening questionnaire (HPSQ) proved to be good tool for identification of DD [8, 11]. HPSQ comprehends three domains of dysgraphic writing: legibility, performance time and physical and emotional well-being. Questionnaire is designed for parents or teachers who are reporting about participating children.

Computerized system methods [3] build on digitizing tablets can assess written product objectively and more accurately than in the manual approach [1, 6, 7, 9, 12, 13]. For instance, recent studies show that children with DD can be automatically diagnosed with up to 90 % accuracy [10]. The digitizing tablets enable us to acquire spatiotemporal information and therefore we call the recorded handwriting as online. Moreover, it is possible to track a movement of pen when it touches surface (on-surface) as well as when the tip of pen is up to 1 cm above it (in-air).

The first objective of this paper is to identify features extracted from three different tasks that significantly correlate with score of HPSQ. The second objective is to explore and find features that are alone biomarkers of DD.

2 DATASET AND METHODOLOGY

2.1 DATASET

64 participants (age 9.19±0.66 years) were enrolled for this study. Based on cut-off score of the HPSQ questionnaire, the children were divided into two groups: experimental (9 girls, 20 boys) with HPSQ = 22.17±2.77, and comparative (10 girls, 25 boys) with HPSQ = 4.74±2.37. All of them were right-handed writers. 25 children attended third and the rest fourth class of the elementary school. Their grades were 1.41±0.56. The study was approved by the local ethics committee, and parents of all the children signed an informed consent form.

2.2 DATA ACQUISITION

The children were asked to perform 3 tasks: write the Czech alphabet, copy a paragraph and write a few sentences on any theme. During the performance, children were writing on an A4 lined paper (which was lay down and fixed to a digitizer) with an inking wireless electronic pen. More specifically, we used the digitizer Wacom Intuos Pro L (PTH-850) and Wacom inking pen for Intuos 4/5. Following information was collected during writing: position $x[t], y[t]$, in-air/on-surface state $s[t]$, tip pressure $p[t]$, altitude $a[t]$, azimuth $z[t]$. These data were sampled with 100 Hz frequency. Comparison of handwriting performance of representatives with and without DD can be seen on Figure 1.

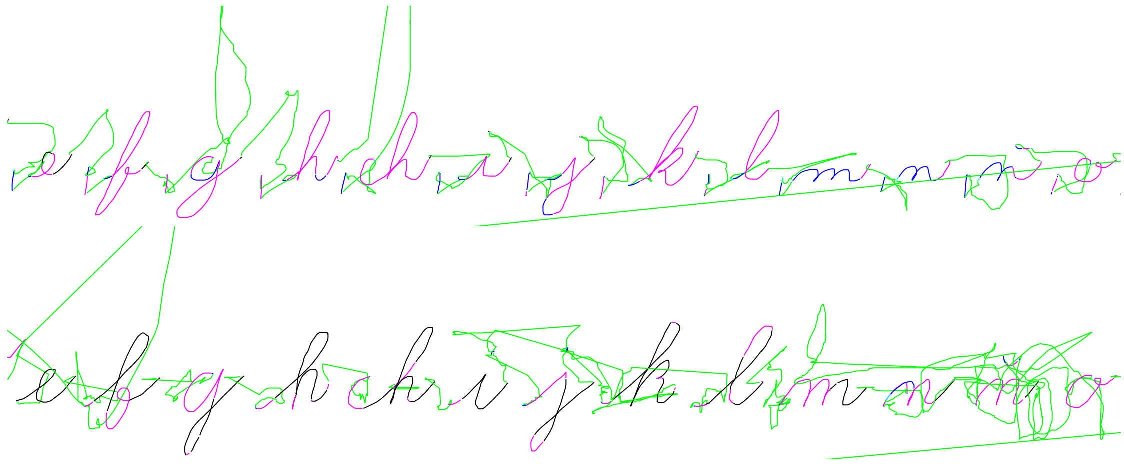

Figure 1: Part of the Czech alphabet written by child withoud DD (HPSQ = 1, upper part of picture) and child with DD (HPSQ = 26, lower part of picture): colour of letters represents normalized tip pressure (0 – 25 % = cyan; 25 – 50 % = blue; 50 – 75 % = magenta; 75 – 100 % = black) and green lines represent the in-air movement.

2.3 HANDWRITING FEATURES

During the parametrization process, we extracted the following handwriting features: spatial (width, height, length), temporal (duration), kinematic (speed, velocity, acceleration, jerk), and dynamic (pressure, azimuth, altitude). In addition, a number of interruptions (in-air/on-surface transition) was calculated. These features were calculated for horizontal and vertical movements separately, moreover, some of the features were calculated from the in-air movement as well. Finally, these statistics were calculated when an original feature was represented by a vector in time: range, mean, mode, standard deviation, percentiles, quartiles, mean excluding outliers, kurtosis, Shannon entropy, etc.

From the overall set of features we further extracted subset of parameters, that are clinically interpretable. Therefore we considered two scenarios: 1) analysis of the whole feature set (all); 2) analysis of clinically interpretable features only (clin).

2.4 Statistical analysis

In the first step we conducted correlation of each computed feature with the score of HPSQ questionnnaire using Pearon's and Spearman's correlation coefficients. Next, in order to check a discrimination power of each feature, univariate binary classification based on random forests classifier was employed (10-fold cross validation with 25 repetitions). The classifier was evaluated by accuracy (ACC), sensitivity (SEN), specificity (SPE) and Matthew Correlation Coefficient (MCC).

3 RESULTS

Results of the correlation analysis are summarized in Table 1. Top four features selected based on their *p*-values are reported for each task. Next, results of the univariate classification can be found in Table 2. In this case, the top four features were selected based on MCC. The most discriminative and clinically interpretable feature for each task is displayed on Figure 2.

Table 1: Spearman's and Pearson's correlations with HPSQ score

Type		Spearman (r)	p	Pearson (ρ)	p
	Alphabet task				
all	harmonic mean of speed of writing (in-air)	-0.435	0.0003	-0.469	0.0001
all	10th percentile of Speed of writing (in-air)	-0.405	0.0009	-0.461	0.0001
clin	min. of Speed of writing (on-surface)	-0.428	0.0004	-0.433	0.0003
clin	duration of writing (in-air)	0.424	0.0005	0.386	0.0016
	Copying paragraph task				
all	interdecile range of horizontal acceleration (in-air)	**-0.501**	**< 0.0001**	**-0.490**	**< 0.0001**
all	90th percentile of horizontal acceleration (in-air)	-0.491	< 0.0001	-0.487	< 0.0001
clin	median of velocity (in-air)	-0.381	0.0019	-0.374	0.0023
clin	min. of length of stroke (in-air)	-0.277	0.0268	-0.368	0.0027
	Free writing task				
all	40th percentile of speed of writing (in-air)	-0.427	0.0004	-0.442	0.0003
all	mean excluding 50 % outliers of speed of writing (in-air)	-0.441	0.0003	-0.434	0.0003
clin	median of speed of writing (in-air)	-0.445	0.0002	-0.433	0.0004
clin	median of width of stroke (in-air)	-0.361	0.0034	-0.386	0.0016

Table 2: Evaluation of binary classification based on random forest

	ACC [%]	SEN [%]	SPE [%]	MCC[-]
Alphabet task				
studentized range of duration of stroke (on-surface)	**76.58±17.34**	**74.79±27.67**	**79.61±23.97**	**0.54±0.35**
mean excluding 20% outliers of vertical normalized jerk (on-surface)	75.61±17.95	74.93±28.31	76.59±24.77	0.50±0.37
mode of azimuth	74.26±16.14	74.81±27.85	75.37±24.53	0.49±0.33
mean excluding 10% outliers of vertical normalized jerk (on-surface)	73.26±16.90	75.68±26.55	71.32±25.65	0.46±0.36
Copying paragraph task				
relative interpercentile range of jerk (in-air)	73.66±17.35	77.73±26.69	69.29±29.47	0.47±0.38
modulation of vertical acceleration (on-surface)	71.57±16.40	75.65±27.80	68.69±25.87	0.44±0.35
kurtosis of Teager Kaiser operator (vertical in-air)	71.79±17.12	75.40±27.29	69.61±26.09	0.44±0.36
pearson's 2nd skewness coeff. of speed of writing (on-surface)	72.49±16.89	66.51±30.60	77.04±24.68	0.43±0.38
Free writing task				
pearson's 2nd skewness coeff. of horizontal velocity (in-air)	72.09±17.45	74.71±29.13	70.02±26.09	0.44±0.38
pearson's 1st skewness coeff. of horizontal velocity (in-air)	71.38±17.40	73.54±29.01	70.88±27.94	0.43±0.37
first correlation coefficient of pressure	71.23±17.91	71.73±28.71	72.08±26.87	0.42±0.37
20th percentile of speed of writing (in-air)	70.31±17.91	62.92±29.39	78.38±24.56	0.41±0.37

4 DISCUSSION

In the first task (alphabet) the harmonic mean of speed of writing (in-air) proved to be feature with the highest negative linear relationship ($\rho = -0.469$). From the clinically interpretable fea-

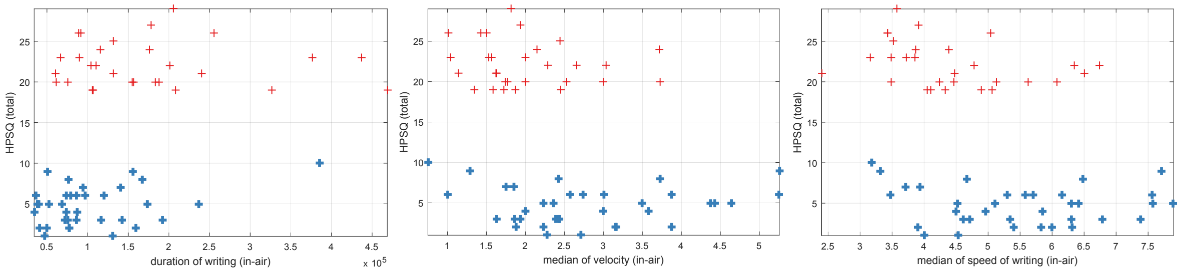

Figure 2: Scatter plot of duration of writing (in-air), median of velocity (in-air), median of speed of writing (in-air) vs. HPSQ total score (healthy subjects are marked by blue colour, dysgraphic by red colour).

tures the minimum of speed of writing also showed strong negative relationship. At last the duration of writing (in-air) had slightly lower but still strong enough linear relationship with HPSQ scores. This shows that children with dysgraphia are spending more time in-air with their writing hand than the healthy children (also this feature is plotted via scatter plot on Figure 2). Studentized range of duration of stroke (on-surface) was the most discriminative feature with ACC = 76.58 % (SEN = 74.79 %, SPE = 79.61 %).

Interdecile range of horizontal acceleration (in-air) was selected as the feature with the highest negative linear relationship with HPSQ score ($\rho = -0.490$) in the second task (copying paragraph). Thanks to the strong negative monotonic relationship of median of velocity (in-air) ($r = -0.381$) with HPSQ score we can conclude that subjects without DD have faster movement of hand in-air than dysgraphic children. The highest value of classification accuracy in this task had the relative interpercentile range of jerk (in-air) with value 73.66 % (SEN = 77.73 %, SPE = 69.29 %).

As in the first task features related to the speed of writing (in-air) were significant in the free writing. The strongest negative relationship had the 40th percentile of speed of writing (in-air) ($\rho = -0.442$). Also the median of speed of writing (in-air) had high absolute value ($\rho = -0.433$). Pearson's 1st and 2nd skewness coefficient of horizontal velocity (in-air) had the highest classification accuracy (71.38 % and 72.09 %, respectively) in this task (SEN = 73.54 %, SPE = 70.88 %; SEN = 74.71 %, SPE = 70.02 %).

5 CONCLUSION

The aim of this study is to identify features that could sufficiently differentiate healthy and dysgraphic handwriting. Based on the correlation analysis, we conclude that the temporal and kinematic parameters have significant discrimination power. Moreover, using just very simple univariate classification in combination with a temporal parameter, we are able to identify DD with 75 % sensitivity and 80 % specificity. These results accent the impact of quantitative online handwriting analysis in this field of science.

This study has a pilot character and several improvements can be done. First of all, it is expected that a multivariate classification in combination with some feature selection techniques could significantly improve the results. Next, to better rate the dyshraphia, binary classification should be replaced by some regression methods, e.g. by classification and regression trees or by extreme gradient boosting algorithms. Finally, to be able to generalize the results, a bigger dataset must be analysed.

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